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Dairy productivity and climatic conditions: econometric evidence from South-eastern United States

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Climate change and food security have become critical issues in the agricultural policy agenda. Although global warming is expected to increase both the frequency and severity of heat stress on dairy cattle, there are very few economic studies focusing on this issue. This paper contributes to the literature by integrating the frontier methodology, commonly used in applied production economics, with heat stress indexes used by animal scientists but largely ignored by economists. Our econometric models are useful to quantify gross benefits expected from adaptation to climatic conditions represented by the Temperature Humidity Index (THI) and alternatively by the Equivalent Temperature Index (ETI). Stochastic production frontier analysis is used to measure technical efficiency for an unbalanced panel of 103 dairy farms located in Florida and Georgia. Five alternative model specifications are evaluated. The results reveal that both THI and ETI have a significant nonlinear negative effect on milk production. The climatic indexes when incorporated in the frontier specification absorb some of the output shortfall that otherwise would be attributable to inefficiency. The results indicate that using fans combined with sprinklers is an effective adaptation to offset output losses stemming from heat stress conditions.

Keywords: dairy farm, heat stress, panel data, stochastic frontier.

1. Introduction

In spite of steady technological advancements in agriculture, climate remains a limiting factor in farm production. As Barrios *et al.* (2008) point out, it is not only dramatic natural hazards, such as droughts and floods, that have adverse consequences on agricultural production, but small changes in climatic conditions can also have substantial impact when farmers are not well equipped to deal with such change. Thus, climate change has become increasingly important in discussions concerning food security and agricultural policies (FAO 2008).

The implication of climate change induced weather variability to the food system is a growing research area, and a considerable volume of the literature

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has been building over the last two decades. Observed and potential negative shocks on crop yields and returns (Jones and Thornton 2003), and profitability of livestock farming (St-Pierre *et al.* 2003) are among the indicators that have been reported in the literature for various parts of the world. The Food and Agriculture Organization (FAO) warns that global warming will have grave adverse effects on the key dimensions of food security including food availability, food accessibility, food utilization and food system stability (FAO 2008). This same report calls for policy actions to safeguard food security in a changing climate by increasing agricultural productivity and avoiding production losses that could result from rising temperature, changing rainfall patterns and new pests and diseases.

The fact that livestock farming is particularly sensitive to weather extremes (e.g. heat waves) is well documented. St-Pierre *et al.* (2003) computed economic losses faced by the livestock industry in the United States and their results reveal dairy subsector losses ranging from $897 million to $1500 million annually owing to heat stress. In the recent past, sporadic weather patterns and an increase in the frequency of extreme hot summer days have been documented and attributed to climate change (Frumhoff *et al.* 2007). Even for good managers, these random shocks may lower productivity and profits, which presents a major challenge to the dairy farming sector, where profit margins are tight. Adoption of available and emerging technologies to counteract these effects is crucial, but these actions depend on farmers' perceptions and knowledge.

Thus, two issues that have become crucial for dairy farm sustainability are: (i) localized assessments of heat stress risk and potential adaptation strategies; and (ii) improving managerial performance, often measured by technical efficiency (TE), which is a key component of productivity (Coelli *et al.* 2005). Despite the documented negative effect of heat stress on dairy productivity, a review of the related economics literature has yielded no study focusing on the association between heat stress, milk production and efficiency. This study contributes to the literature by bringing together the stochastic frontier methodology, which has become very popular in agricultural productivity studies (Bravo-Ureta *et al.* 2007), with climatic indexes used by animal scientists but largely ignored by economists. The advantage of using these indexes in production models is that they incorporate the key climatic variables (e.g. temperature and humidity) in a parsimonious fashion. This study focuses on the potential impact of heat stress on milk production efficiency for a sample of dairy farms from the south-eastern US. Moreover, we are also able to quantify the gross benefits associated with adaptation practices, which are readily available to producers but not adopted by all. The analyses will show that such adaptation can make a significant contribution to gross farm income.

The remainder of this article is structured as follows: section 2 provides an overview of the growing world dairy sector and the link between climatic conditions and milk production; section 3 furnishes information on the climatic conditions of the study area and its dairy farming industry; section 4 presents our analytical framework and related literature; section 5 presents the data and empirical models; section 6 takes up the results, followed by a discussion of policy issues; and section 7 concludes.

2. The world dairy sector in a changing climate

As global per capita income rises, the demand for protein relative to carbohydrates is also increasing, and people are consuming growing quantities of meat and dairy products. Simulation studies project that a 1.8°C rise in mean global temperature, a lower bound according to the Intergovernmental Panel on Climate Change (IPCC), would lead to a 1.39 per cent decline in livestock production in Southeast Asia, and that a larger increase in mean global temperature would have more severe effects (Darwin 2001). Darwin also speculates that to meet the rising demand for dairy products, global milk production will need to grow by about 2 per cent per year.

Dairy cows need an optimum range of atmospheric conditions to be most productive. Scientific studies have established that heat stress events are associated with a combination of environmental factors such as temperature, humidity, solar radiation and wind speed (Silva *et al.* 2007). While wind eases the impact of high temperature, solar radiation amplifies it and several indexes have been proposed to integrate these factors. However, the variables that are extensively used as indicators of heat stress are temperature and humidity because data on other factors are usually not readily available. The Temperature Humidity Index (THI) has gained popularity among animal scientists as a means of quantifying discomfort levels caused by heat stress (Bohmanova *et al.* 2007). The THI is a function of air temperature and humidity, integrating both of their effects into a single number. Traditionally, it is thought that dairy cattle show signs of mild (moderate) heat stress and milk production is reduced when the THI crosses a critical threshold of 72 (78). The Equivalent Temperature Index (ETI), another less commonly used alternative, incorporates the wind effect along with air temperature and humidity. According to Silva *et al.* (2007), ETI can outperform THI in analysing heat stress effects in hot and humid climates.

The impact of heat stress on milk production has been established based on farm records, experiments and simulation studies. Table 1 presents selected heat stress studies from different climate zones and continents using observed data. Simulation studies predict potential losses for dairy farmers from climate change in the future. A projection study for the north-eastern US (Frumhoff *et al.* 2007) warns that by the end of this century, under a higher emissions scenario, Connecticut, Massachusetts, New York and Pennsylvania will reach a mean temperature during the summer months that might reduce milk production by 10–20 per cent or more. Another risk assessment study developed for Australia (Jones and Hennessy 2000) predicts that herds without shade protection could face up to a 4 per cent decline in annual

Table 1 Heat stress impact studies

Articles	Study area	Result
André *et al.* (2011)	Netherlands	Annual loss of 31.4 ± 12.2 kg of milk/cow
Barash *et al.* (2001)	Israel	Loss of daily milk yield = 0.38 kg/1°C rise in temperature
Bohmanova *et al.* (2007)	United States	Yearly loss in milk yield ranges from 100–168 kg
Ageeb and Hayes (2000)	Sudan	Daily milk yield loss = 0.29 ± 0.04 kg per unit THI
Valtorta *et al.* (2002)	Argentina	Daily milk yield loss = 0.25 l per unit THI
Mayer *et al.* (1999)	Australia	Annual loss in milk yield ranges from 59 to 103 L
Bryant *et al.* (2007)	New Zealand	1 unit rise of THI (3 day average > 68) causes milk solid loss of minimum 10 g/cow/day

Note: THI, Temperature Humidity Index.

production; however, adaptation in dairy management practices could limit the damage to 1 per cent by 2030. Taken together, these findings underscore the challenges posed by climatic conditions on dairy farming as global warming is expected to increase both the frequency and the severity of summer heat stress for dairy cattle in many parts of the world.

3. Study area

This study focuses on Florida and Georgia – two states in the south-eastern US. Florida's climate is classified as subtropical and, except for the mountainous northern part of the state, Georgia falls in the same climate zone. Northern Florida is cooler in the winter because of its latitude, whereas the southern part is characterized by longer periods of high temperatures and high humidity. Summers throughout the state are long, warm and fairly humid. Winters are mild, with periodic episodes of cool to occasionally cold air. Florida (Georgia) is ranked 1st (5th) among all the United States in heat stress events, characterized by an average 4261 (2765) hours/year of heat stress conditions, while the comparable figure for the United States as a whole is a weighted average of 1218 (St-Pierre *et al.* 2003). In Florida and Georgia, rainfall can fluctuate greatly from year to year among counties, and serious droughts have occurred. Both states experienced harsh statewide droughts from 1998 to 2002 and again from 2006 to 2007.

Results of simulation models from the IPCC (2007) suggest that the severity of climate change will vary across the United States, but the southern part of the country is expected to be hard hit. Fraisse *et al.* (2008) noted that the states of Alabama, Florida and Georgia have experienced a rise in average annual temperatures since 1980, but rainfall changes were less pronounced.

The same authors mentioned that models build by the Hadley Centre for Climate Prediction and Research projected increases of 1.3 and 0.6°C in the maximum summer and winter temperatures, respectively, and a 3 per cent rise in precipitation in the south-eastern US by 2030.

Two decades ago, Sharma *et al*. (1988) analysed historical data from the University of Florida Agricultural Experiment Station herd and documented noteworthy interactions between climate effects and milk yields and composition. Utilizing a simulation study, Klinedinst *et al*. (1993) indicated that the greatest potential decline in summer season milk production would occur in the southeast and the southwest parts of the nation. In a simulation study based on US cow inventories and production data for the year 2000 and historical weather data, St-Pierre *et al*. (2003) estimated that in Florida, heat stress is responsible for milk production losses amounting to 1803 kg per cow per year and a death rate of 1.72 per cent per year. Using seven versions of THI computed with data from nearby weather stations and farm records from Georgia, Bohmanova *et al*. (2007) measured the marginal effect of THI on annual milk yield.

Bucklin *et al*. (2008) noted that sprinkling combined with fans is the most commonly used cooling technique in Florida. They also reported results from a cooling effectiveness study carried out at the University of Florida's Agricultural Experiment Station. The cows under a freestall shade structure with sprinkling and fan system produced 4.6 lbs more milk per day (an 11.6 per cent increase in milk production) than those under a noncooled structure. Smith and Ely (1997) also found statistical evidence that Georgia Holstein herds housed in freestall barns produced more milk. Even with the use of sprinklers and fans, however, mild to moderate heat stress is observed in dairy cows during much of the spring, summer and fall. In sum, a major challenge facing dairy farmers in the south-eastern US is heat stress which requires the analysis and formulation of adaptation options.

Florida dominates milk production in the south-eastern US, followed by Georgia. In 2009, Florida (Georgia) ranked 19th (25th) in the continental US for milk production. The dairy sector in these two states is dominated by relatively large farms. In 2007, 90 per cent (50 per cent) of total milk production in Florida (Georgia) came from large dairy herds (with more than 500 heads) containing 88 per cent (46 per cent) of the milk cow inventory of the respective state. The number of dairy cows in Florida (Georgia) has decreased at an annual rate of 2.07 per cent (1.63 per cent) since 1995, while the quantity of milk per cow has increased by 1.63 per cent (1.20 per cent) annually reaching 18,070 (18,182) lbs in 2009. Even though these states are small players in the US dairy industry, dairy farming has a significant role in their economies. Recognizing this importance, the University of Florida initiated the Dairy Business Analysis Project (DBAP) in 1995 to document the financial performance of the state's dairy farms using standardized accounting measures. The University of Georgia joined the effort in 1998 (Source: http://edis.ifas.ufl.edu/an249).

4. Analytical framework

In this study, we adopt a panel data version of the stochastic production frontier (SPF) approach to study TE for a sample of dairy farms. The general model can be written as:

$$Y_{it} = X_{it}\beta + v_{it} - u_{it} \tag{1}$$

where Y_{it} denotes output for the *i*th farm in the *t*th time period; X_{it} denotes a $(1 \times \mathrm{K})$ vector of inputs and other explanatory variables for the *i*th farm in the *t*th time period; β is a $(K \times 1)$ vector of unknown parameters to be estimated; v_{it} is a random error, with $v_i \sim iid\ N(0,\sigma_v^2.)$ and independent of u_{it}; and u_{it} is a non-negative, independently distributed random error associated with the technical inefficiency of the *i*th farm. The inefficiency term can have various specifications, and we implement here the Battese and Coelli (1995) time-varying inefficiency model given by:

$$u_{it} = Z_{it}\delta + w_{it} \tag{2}$$

where Z_{it} is a set of variables explaining technical inefficiency, and w_{it} is defined as a truncation of a normal distribution with mean 0 and variance σ_w^2. Technical efficiency for each observation can be computed by the expression:

$$\mathrm{TE}_{it} = \exp(-u_{it}|v_{it} - u_{it}) \tag{3}$$

The production economics literature has emphasized that the '…ability of a manager to convert inputs into outputs is often influenced by exogenous variables that characterize the environment in which production takes place' (Coelli *et al*. 2005, p. 281). However, very few agricultural productivity and efficiency studies incorporate the role of environmental conditions. Demir and Mahmud (2002) contend that economists typically assume that environmental conditions are captured by the two sided random error (v) in stochastic frontiers, even though the expected value of such conditions is known to farmers and hence is not purely random. Moreover, these authors were one of the first to recognize that the exclusion of environmental factors may lead to biased TE scores. Another early contribution to this literature is by Sherlund *et al*. (2002) who incorporated rainfall, soil fertility and slope into an SPF model for rice in the Côte d'Ivoire. A few years later, Barrios *et al*. (2008) assembled a large panel data set where they integrated FAO country level information with IPCC data to estimate econometrically a production function model. These authors showed that climate change, through increases in temperature and rainfall variability has had a significant adverse impact on agricultural output in sub-Saharan Africa.

In the case of dairy farming, there is a sizable volume of work examining productivity and efficiency (Moreira Lopez and Bravo-Ureta 2009) but no study was found that incorporates heat stress conditions in the model. More general specifications attempting to capture climatic conditions in dairy production functions include the work of Moreira *et al*. (2006) who incorporated agro-climatic zone dummies for Chile, and the work by Kompas and Che (2006) who controlled for drought conditions in Australia, again using a dummy variable.

Consistent with results in the dairy science literature, it is reasonable to assume that climatic conditions represented by THI or ETI may impact the production technology; hence, these factors should be included in the production function. Accordingly, the dairy production frontier to be modelled here can be denoted as $Y = f(X, T, H)$, where X is a vector of conventional inputs, T accounts for technological progress, and H is a heat stress index which is usually omitted as already established. If H plays a significant role in explaining the variation in output and is excluded from the model, then the frontier parameter estimates will generally be biased. Figure 1 depicts this omitted variable problem in a two-period single input, single output model where the base period production frontier is given by F_{base}. In the second period, technological progress has a positive effect on output while higher heat stress has a negative impact and omitting H results in a downward bias in the rate of technological progress. In Figure 1, this is represented by the frontier $F_{H\ \text{omitted}}$ where the gain owing to technical progress is lower compared to the 'true' gain as portrayed by frontier $F_{H\ \text{included}}$. Once H is included in the frontier, the estimated parameters for technological progress will be net of climatic

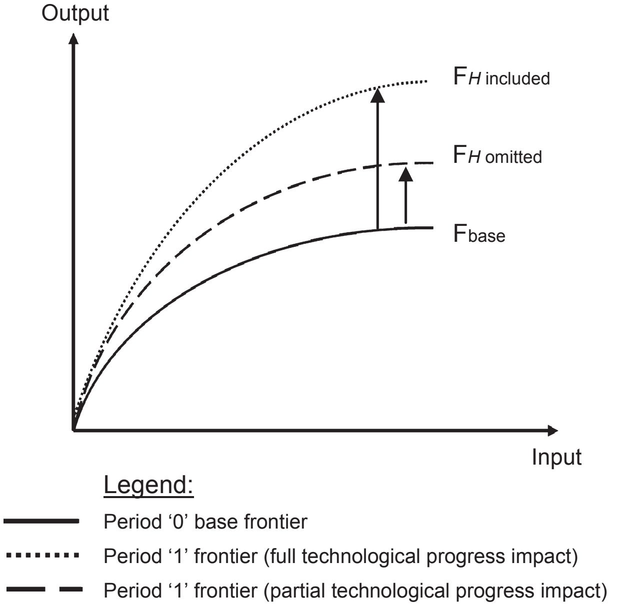

Figure 1 Production frontier shifts because of technological change and heat stress.

conditions. So, we include such an index, THI or ETI, in our dairy production frontier model.

5. Data and models

We utilize farm-level financial and production data collected by the DBAP for Florida and Georgia. Dairy producers are given the opportunity to participate in DBAP, so participants constitute a nonrandom sample of dairy farms, a feature that is common to many dairy farm productivity studies. The accounting methods follow the recommendations made by the Farm Financial Standards Council so all revenues and expenses are expressed on an annual accrual basis; thus, cash receipts and expenses are adjusted for changes in inventory, prepaid expenses, accounts payable and accounts receivable. The data constitute an unbalanced panel including 103 dairy farms, 77 in Florida and 26 in Georgia, sharing data from 1995 to 2008 for a total of 419 observations. Only two farms are present in the data in all years while 25 farms appear just once. One outlier and two additional observations with missing data are dropped. Figure 2 depicts the spatial distribution of the farms in the sample along with the locations of the weather stations used for collecting the climatic data.

Our general production function model can be expressed as $Y = f(X_1, X_2, X_3, X_4, D_1, D_2, D_3, T, \text{ETI or THI})$ where:

Y = annual milk sold per farm (in lbs)
X_1 = average annual number of dairy cows
X_2 = annual feed use
X_3 = full time equivalent (FTE) workers
X_4 = capital flow
D_1 = 1 if the farm uses bovine somatotropin (BST) growth hormone, 0 otherwise
D_2 = 1 if the farm shelters the cows in freestall barn, 0 otherwise
D_3 = 1 if the farm uses fans and sprinklers as a cooling system, 0 otherwise
T = time trend to proxy technological change
ETI/THI = heat stress indexes defined earlier

As already noted, all farm-level variables are constructed or extracted directly from the DBAP data. Annual feed use, measured in dollars, is the sum of annual expenditures on concentrate feed, forage and other feeds. The capital flow is given by the yearly expenses on building, land and machinery and is derived by multiplying the reported building, land and machinery cost per cwt of milk by the total quantity of milk sold. The feed and capital use variables are expressed in constant dollars, by deflating them by the producer price index for dairy cattle feeds and for agricultural machinery, respectively. The three dummy variables (D_1, D_2 and D_3) are included to capture some key technical characteristics of the farm.

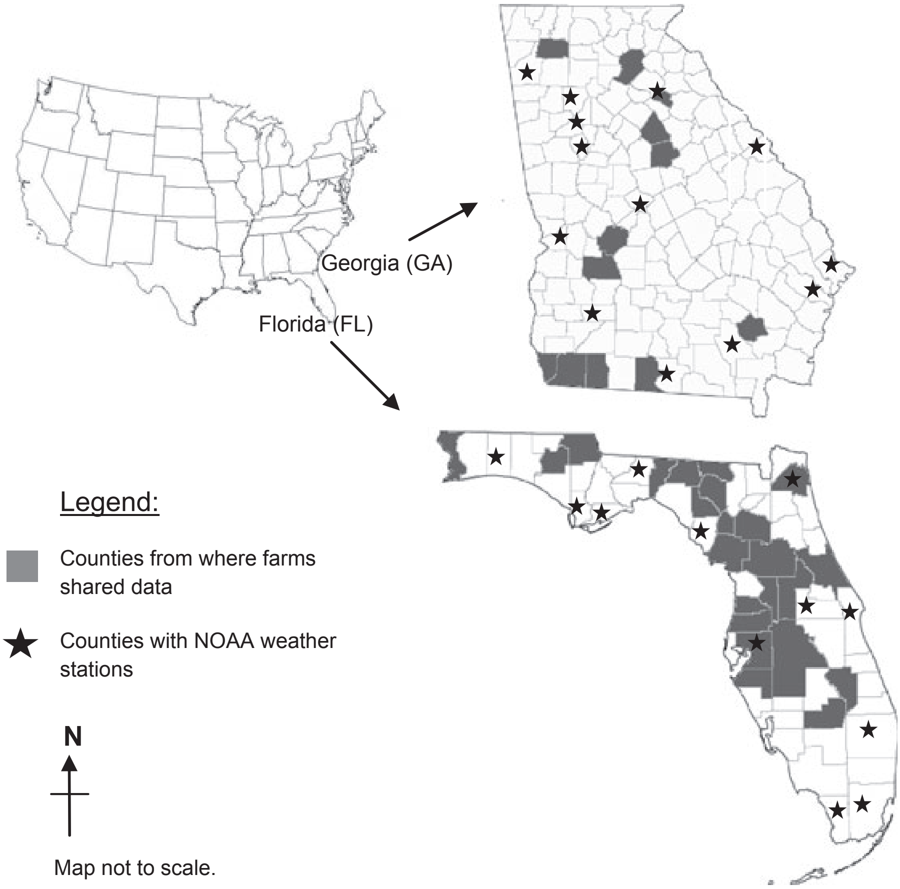

Figure 2 Spatial distribution of dairy farms reporting to Dairy Business Analysis Project and National Oceanic and Atmospheric Administration weather stations.

As indicated, to investigate the effects of climatic conditions, we have considered two alternative variables, the annual means for THI and ETI. Data on atmospheric variables from the National Oceanic and Atmospheric Administration's (NOAA) National Climatic Data Center (NCDC) have been matched with the dairy data. The NCDC database stores daily observations from various weather stations on maximum, minimum, average and dew point temperatures, wind speed and total precipitation. After some necessary adjustments, these weather data are used to generate daily THI and ETI using the equations (Bohmanova *et al*. 2007; Silva *et al*. 2007):

$$\mathrm{THI} = 41.2 + T_a + 0.36\, T_d \tag{4}$$

$$\begin{aligned}\mathrm{ETI} = {} & 27.88 - 0.456\, T_a + 0.010754\, T_a^2 - 0.4905\, U_r + 0.00088\, U_r^2 \\ & + 1.1507\, V - 0.12645\, V^2 + 0.019876\, T_a U_r - 0.046313\, T_a V\end{aligned} \tag{5}$$

where T_a is dry bulb temperature (usually referred to as air temperature in °C), T_d is dew point temperature (in °C), U_r is relative humidity, and V denotes wind speed (measured in meters/second).

Farm observations are available on an annual basis, so the daily calculations of the indexes are averaged to obtain annual figures to match the farm data. Unfortunately, weather data are not available for some counties and in such cases interpolation is used based on information from neighbouring counties in the same climatic zone. After a matching exercise between the DBAP data and the NOAA climatic information, a total of 413 observations are available for the analysis. Pair-wise correlations between annual mean THI and ETI are 0.97 and 0.96 for Florida and Georgia respectively, over the period of the study. To illustrate the variation in climatic conditions over the study region, Clarke (Georgia) – the most northern county, and Hillsborough (Florida) – the most southern county in our data set with a NOAA station, are chosen for a comparison. Average of annual mean THI in the study period (1995–2008) is 61.37 for Clarke and 71.02 for Hillsborough, revealing considerable climatic variability within the study area, a feature that is helpful for econometric estimation.

The Battese and Coelli (1995) model employed in this study makes it possible to estimate both the frontier and the inefficiency as a function of relevant variables in one step. Previously, authors have used a variety of variables including farmer age, education, experience and farm size among others to model inefficiency (e.g. Brümmer and Loy 2000). However, because of data limitations in this study, we only include farm size and consulting expenses per cow (in constant dollars) in the inefficiency effects part of the model. There is no uniform definition of farm size, but a commonly used variable in dairy studies is dairy herd size (e.g. Sumner and Wolf 2002), which is our choice here.

Table 2 shows descriptive statistics for key variables separately for each state and the full sample. Some salient characteristics of the full sample include: (i) high degree of specialization where 90 per cent of farm revenues come from milk sales; (ii) predominance of large farms with an average of 1153 dairy cows; and (iii) average annual milk production per cow of 17,260 lbs. Annual average inputs per farm include \$2038 for feed per cow and \$400 for building, land and machinery use per cow. It is interesting to note that the Georgia farms used BST, the fan-sprinkler combination referred to hereafter as cooling system, and freestall barns more often and spent more on consultants than their counterparts in Florida.

Several SPF models are estimated, all relying on the Translog (TL) functional form. We follow the common procedure of normalizing all variables by their geometric mean, which makes it possible to interpret the first-order parameters directly as partial output elasticities (Coelli *et al.* 2003). Our base model specification (Model I) does not incorporate any information on climatic factors and is given by:

Table 2 Descriptive statistics for Dairy Business Analysis Project (DBAP) data

Variable	Arith. Mean	Geo. Mean	Minimum		Arith. Mean		Maximum	
	Full sample	Full sample	FL	GA	FL	GA	FL	GA
Milk (lbs per cow)	17,260	16,923	6538	9593	16,607	19,103	24,729	26,063
Share of milk sales in total revenue (%)	90.3	90.1	64.0	63.9	90.7	89.4	99.9	99.9
Number of cows	1153	681	53	92	1305	725	11,751	3699
Labor (FTE)	21	13.1	1.3	0.8	23.8	13.2	168	64
Feed expenses/ Cow (in $*)	2038	1956	572	393	2086	1903	4600	3893
Building, land and machinery cost/ Cow (in $*)	400	353	68	117	366	497	999	1310
Consultation expenses /Cow (in $*)	8.9	15.6	0	0	8.3	10.6	127.6	91.3
BST use (%)	55.4	–	–	–	47.5	77.7	–	–
Fan and sprinkler (%)	50.6	–	–	–	40.3	79.6	–	–
Freestall (%)	35.5	–	–	–	29.3	51.8	–	–

Note: Full sample = 413; FL = 305; GA = 108; *Expressed in 2010 USD; FTE, full time equivalent.

$$
\begin{aligned}
y_{it} = \beta_0 + \sum_{k=1}^{4} \beta_k x_{kit} + 0.5 \sum_{k=1}^{4} \sum_{j=1}^{4} \beta_{kj} x_{kit} x_{jit} + \sum_{k=1}^{4} \theta_k x_{kit}\, t \\
+ \theta_5 t + \theta_6 t^2 + \sum_{p=1}^{3} \alpha_p D_{pit} + v_{it} - u_{it}
\end{aligned} \tag{6}
$$

where the subscript k (p) refers to the kth input (pth dummy) and lowercase indicates that the variable has been normalized by the geometric mean. Then, climatic conditions are introduced through the two alternative variables already discussed: THI (mean corrected) in Model II, and ETI (mean corrected) in Model III. Models II and III have linear and quadratic terms of the respective index to capture possible nonlinear effects. To examine whether the adaptation dummies jointly reduce the impact of heat stress, we estimate two additional models, II-NA and III-NA (NA: No adaptation), excluding D_2 and D_3.[1]

[1] Following one of the suggestions from an anonymous reviewer, we tested whether the production technology across the two states is the same (e.g. Battese *et al*. 2004). The results of this test indicate that the technology across the two states is different from a statistical point of view. However, the estimates based on the Georgia data alone are not consistent with prior expectations, which is likely due to the fact that we only have 108 observations for this state. Moreover, recent evidence from the dairy science literature indicates that commercial dairy farming practices across the Southeastern US are very similar (Webb 2011). Therefore, we contend that the more robust specification from an economic stand point is the pooled model, i.e., including the data from both states in one model.

6. Empirical results

Following the estimation of five SPF models, we discard models III and III-NA because little improvements are exhibited over II and II-NA and the latter incorporate the more commonly used THI index. The parameter estimates for the selected models are presented in Table 3. All models satisfy the regularity conditions, at the sample geometric mean, required for a production function to be consistent with economic theory. Also, Model II outperforms Model I and II-NA, as per Likelihood-Ratio (LR) tests at 1 per cent level of significance.

Table 3 Maximum likelihood estimates of alternative production frontier models

Models (N = 413)	Model I		Model II		Model II-NA	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Intercept	0.330***	0.042	0.050**	0.025	0.088***	0.023
x_1 (Cow)	0.487***	0.031	0.575***	0.032	0.575***	0.033
x_2 (Feed)	0.279***	0.025	0.271***	0.025	0.268***	0.025
x_3 (Labor)	0.050**	0.020	0.067***	0.019	0.078***	0.018
x_4 (Capital)	0.101***	0.014	0.066***	0.013	0.074***	0.014
t (Trend)	0.005***	0.002	0.009***	0.002	0.013***	0.002
0.5 x_1^2	0.167	0.130	0.231*	0.125	0.214*	0.126
0.5 x_2^2	0.285***	0.076	0.253***	0.076	0.247***	0.078
0.5 x_3^2	−0.072	0.056	−0.067	0.054	−0.055	0.053
0.5 x_4^2	0.003	0.036	−0.010	0.034	−0.028***	0.035
0.5 t^2	0.002*	0.001	0.001	0.001	0.000	0.001
x_1x_2	−0.269***	0.090	−0.264***	0.083	−0.256***	0.086
x_1x_3	−0.019	0.056	0.007	0.054	−0.006	0.055
x_1x_4	0.105*	0.058	0.049	0.055	0.064	0.057
x_2x_3	0.055	0.062	0.037	0.060	0.034	0.059
x_2x_4	−0.118**	0.045	−0.078*	0.043	−0.078*	0.044
x_3x_4	0.002	0.035	0.043	0.033	0.053	0.034
x_1t	0.007	0.008	0.016**	0.007	0.016**	0.007
x_2t	−0.008	0.007	−0.008	0.007	−0.007	0.007
x_3t	0.004	0.005	0.005	0.005	−0.005	0.005
x_4t	−0.005	0.003	−0.005	0.003	−0.003	0.003
D_1 (BST)	0.071***	0.014	0.051***	0.013	0.056***	0.013
D_2 (Freestall)	0.035**	0.016	0.025	0.016		
D_3 (Cooling)	0.107***	0.015	0.050***	0.015		
THI			−0.018***	0.003	−0.022***	0.002
0.5 THI^2			0.002**	0.001	0.003**	0.001
Inefficiency effects						
Intercept	0.541***	0.048	0.304***	0.060	0.294***	0.061
Z_1 (consulting)	−0.002***	0.000	−0.003**	0.001	−0.002**	0.001
Z_2 (cow)	−0.122***	0.019	−0.398***	0.147	−0.417***	0.144
Z_3 (cow^2)	0.000	0.001	0.030***	0.011	0.003***	0.011
γ	0.904***	0.102	0.679***	0.086	0.623***	0.079
Log-likelihood	309.57		338.44		330.62	
LR statistic	32.76		31.21		31.81	

Note: *10% level of significance; **5% level of significance; ***1% level of significance; SE, Standard error; THI, Temperature Humidity Index.

The partial output elasticity estimates, that is, the linear terms in equation (6), at the geometric mean for all inputs are highly significant across the models. A noteworthy observation, however, is that the partial elasticity of cow is approximately 9 per cent points higher in Models II and II-NA compared to Model I. The sum of the partial output elasticities, that is, the function coefficient (FC), is the indicator commonly used to measure economies of size in primal models, as the ones reported here. In Model I, the value of the FC is 0.92, suggesting decreasing returns to size at the geometric mean. However, inclusion of THI raises the FC to 0.98 in Model II, which is quite close to constant returns. The sign of the coefficient associated with the BST dummy is consistently positive and significant; however, the magnitude of this positive effect goes down once THI is incorporated. The effect of technological progress, at the geometric mean, is significant in all cases and the magnitude goes up to 0.90 per cent per year in Model II from 0.50 per cent in Model I, which is consistent with the previous discussion in Section 4 and the illustration in Figure 1. The 0.90 per cent annual growth rate is within the range reported in other dairy studies that use a smooth time trend (e.g. 1 per cent in Ahmad and Bravo-Ureta 1996).

We now discuss the findings regarding two issues central to this study, namely, the impact of heat stress on milk output and the effectiveness of adaptation. The first-order (second-order) parameter of THI is significant and negative (positive) in Models II and Model II-NA, denoting a decreasing marginal effect of mean annual THI on output.[2] The negative association between THI and milk production is consistent with dairy science studies (e.g. Bohmanova *et al*. 2007). A comparison of the THI coefficients across models II and II-NA establishes that the cooling system and a freestall barn reduce the negative effect of heat stress on milk production. The sign of the coefficients associated with cooling and freestall are also positive and significant in Model I. However, the magnitudes of these positive effects diminish noticeably and freestall turns out to be statistically insignificant once THI is incorporated.

Model II is utilized to evaluate the change in milk output in response to two possible adaptation strategies. To serve as a benchmark, frontier output is computed at the geometric sample mean of all inputs (Table 2), THI is set at 68.3 (sample mean), D_1 is set to 1, T is fixed at 7, the mid-point between the time span analysed (1995–2008), and the cooling system (D_3) and freestall (D_2) dummies are held at zero. In contrast, frontier output is recalculated setting $D_2 = 0$, $D_3 = 1$ (Case A) and then fixing $D_2 = D_3 = 1$ (Case B), that is, the latter corresponds to a farm with a freestall barn and cooling system. For the benchmark scenario, the average farm has an annual milk production per cow equal to 18,689 lbs. In contrast, Case A exhibits a gain of 963 lbs (5 per cent), while the gain for case B amounts to 1466 lbs (7 per cent) per cow. We should point out that the estimated yield increase for Case B is

[2] The linear parameter for THI quantifies the percentage change in milk output because of a unit increase of the variable, evaluated at the sample mean.

comparable to what is reported in Bucklin *et al.* (2008). These alternative scenarios are used to illustrate the effects of the cooling system and a freestall barn on a hypothetical farm where all inputs are set at their geometric means of the data and the price of milk is set at \$16.29, which is the average received by farmers in the United States in 2010. The annual increase in gross revenues for this farm is estimated at \$106,830 and \$162,631 for cases A and B, respectively. Further insight on the sensitivity of the gross benefits accruing from the cooling strategy in the presence of freestall barns, can be found in Table 4. The results clearly show an inverse relationship between yield benefit and THI irrespective of farm size and that benefit initially increases and then decreases with herd size.

Now turning to TE, the first point to note is that the relevant t statistic suggests a rejection of the null hypothesis that $\gamma = 0$; thus inefficiency is present in all three models (Table 3). The inefficiency effects component in Models II and II-NA reveal further insights. The coefficients for the farm size variable suggest that TE increases with dairy herd size but at a decreasing rate, a finding that is consistent with what is reported by several authors (e.g. Brümmer and Loy 2000; Kompas and Che 2006). The positive impact of having outside consultants on TE is consistent across models and conforms to what would be expected *a priori*. Descriptive statistics for TE scores are provided in Table 5. A comparison of mean TE scores for the various models reveals that average TE increases from 68 per cent in Model I to 90 per cent in Models II and II-NA. This finding is in agreement with Sherlund *et al.* (2002) who concluded that the omission of environmental conditions can result in a marked downward bias in TE estimates. The average TE score of 90 per cent is somewhat higher than the averages reported by Moreira Lopez and Bravo-Ureta (2009) in their meta-analysis of SPF studies for dairy farms.

Table 4 Sensitivity of gain in annual milk yield from fan-sprinkler cooling

Annual mean THI	Number of cows				
	100	500	1000	2000	3000
65.3	664	1059	1105	1046	969
67.3	634	1012	1055	999	926
68.3	622	992	1034	980	908
69.3	611	975	1017	963	892
71.3	595	949	989	937	868

Note: THI, Temperature Humidity Index.

Table 5 Descriptive statistics of technical efficiency scores

	Mean	Median	SD	Minimum	Maximum	Skewness
Model I	0.682	0.666	0.114	0.413	0.991	−0.757
Model II	0.896	0.925	0.082	0.608	0.991	−1.008
Model II-NA	0.899	0.927	0.081	0.617	0.989	−1.066

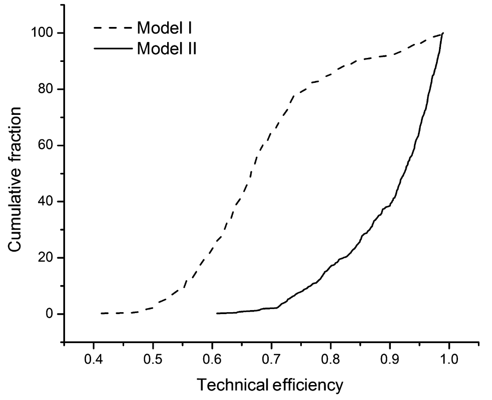

Figure 3 Distribution function of technical efficiency scores (with and without heat stress effect).

To get additional details on how climatic conditions impact TE, we focus briefly on its statistical distribution. The three selected models exhibit negative skewness for TE indicating that the underlying distributions are nonnormal. The Kolmogorov–Smirnov test is carried out to evaluate whether the TE distributions emerging from Models I and II are similar or not. The result of this test shows that the TE distributions are indeed different at the 1 per cent level. According to Figure 3, Model I, which excludes THI, places almost 25 per cent of the sample below the minimum TE obtained from Model II. A closer look at individual TE scores shows that the gain in efficiency is much higher in the lower end of the TE distribution. More specifically, the mean TE for the first (fourth) quartile from Model I is 55 per cent (83 per cent) and goes up to 78 per cent (97 per cent) in Model II. High Spearman's rank correlation (ρ) across models (e.g. between I and II, $\rho = 0.89$) indicate that farm rankings in terms of TE scores are quite similar. This is in contrast with Sherlund *et al.* (2002), who found that inclusion of environmental factors substantially altered not only the level of TE but also the efficiency ranking of individual farms.

7. Conclusions

The effect of heat stress on dairy farms is a matter of growing concern as global warming continues; however, the production economics literature on this subject is quite limited. This study contributes to the existing body of knowledge by integrating the stochastic production frontier (SPF) methodology, frequently applied in economic analysis, with heat stress indexes used by animal scientists but largely ignored by economists. Several SPF models are estimated utilizing a panel of dairy farms located in Florida and Georgia. The results reveal that those indexes have a significant nonlinear negative effect on milk production. Therefore, their omission in the production frontier leads to a misspecification error. Also, incorporating heat stress in the frontier specification reduces some of the output shortfall that otherwise would be attributable to inefficiency. A mean technical efficiency (TE) level equal to 90 per cent, with heat stress included in the frontier, implies that on average there is little room for productivity growth by enhancing managerial skills. In addition, the results show a moderate rate of technological progress, which is even lower when the heat stress factor is ignored. These results suggest that future productivity growth in dairy farming can be hampered by a warmer environment in the region; thus, research that facilitates farmer adaptation to reduce the impact of heat stress is warranted. It is important to note that heat stress can also have an adverse effect on herd reproduction but this is a matter beyond the scope of our study.

Another noteworthy contribution of the article is estimates of the gross benefits associated with the use of fans combined with sprinklers as an adaptation to offset output losses stemming from heat stress conditions. The average estimated gain in gross revenues for a hypothetical farm is \$106,830 per year and this figure rises to \$162,631 when the farm has a freestall barn. Sensitivity analysis reveals an inverse relationship between yield and THI irrespective of farm size and that the benefit of using the cooling system first increases and then declines with herd size. In the light of these results, it is somewhat surprising that about half of the farms in the sample analysed have not adopted this cooling strategy. Investigating the forces behind such adoption/nonadoption is beyond the scope of this study but is a matter that deserves further study. Two specific issues that should be pursued concern the expected rate of return associated with investing on cooling systems and the level of awareness that farmers have concerning the possible benefits of adaptation. The analysis also suggests that as outside consulting services have a positive impact on TE, strengthening of extension services can have a role in enhancing farm performance.

A cautionary note concerns the possible presence of selectivity bias on the decision to adopt or not the cooling system. Recent progress concerning selectivity in frontier models has been made (e.g. Greene 2010; Bravo-Ureta *et al*. 2012). However, no model has been developed to date that incorporates selectivity within the Battese and Coelli (1995) formulation used in this study. This point is raised by Greene (2010) who notes that it warrants consideration in future methodological work.

Finally, O'Donnell *et al.* (2010) show that the methods typically used in efficiency analysis may generate misleading measures of firm efficiency under conditions of uncertainty. To address this problem, the authors propose a state contingent production model and use simulated data to analyse a production process with one nonstochastic input and one stochastic output. Although this approach opens new avenues for further empirical research, many challenges remain including the characterization of states of nature, the probability of their occurrences and coping with the heterogeneity of farm-level behavior. Thus, the authors argue that additional work is needed to develop robust estimation procedures to make it possible to decompose technical efficiency differences from variations arising from the stochastic nature of production.

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